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Remotely Piloted Aircraft for Evaluating the Impact of Frost in Coffee Plants: Interactions between Plant Age and Topography

Gislayne Farias Valente [1,*], Gabriel Araújo e Silva Ferraz [2], Felipe Schwerz [2], Rafael de Oliveira Faria [2], Felipe Augusto Fernandes [1] and Diego Bedin Marin [3]

[1] Program of Graduate Agricultural Engineering, University Federal of Lavras (UFLA), Lavras 37203202, Brazil; fernandesfelipest@gmail.com
[2] Department of Agricultural Engineering, School of Engineering, University Federal of Lavras (UFLA), Lavras 37203202, Brazil; gabriel.ferraz@ufla.br (G.A.e.S.F.); felipe.schwerz@ufla.br (F.S.); rafael.faria@ufla.br (R.d.O.F.)
[3] Agricultural Research Company of Minas Gerais (EPAMIG), Viçosa 36571000, Brazil; diego.marin@ufv.br
* Correspondence: gislayne.valente@ufla.br

Abstract: An accurate assessment of frost damage in coffee plantations can help develop effective agronomic practices to cope with extreme weather events. Remotely piloted aircrafts (RPA) have emerged as promising tools to evaluate the impacts caused by frost on coffee production. The objective was to evaluate the impact of frost on coffee plants, using vegetation indices, in plantations of different ages and areas of climatic risks. We evaluated two coffee plantations located in Brazil, aged one and two years on the date of frost occurrence. Multispectral images were collected by a remotely piloted aircraft, three days after the occurrence of frost in July 2021. The relationship between frost damage and these vegetation indices was estimated by Pearson's correlation using simple and multiple linear regression. The results showed that variations in frost damage were observed based on planting age and topography conditions. The use of PRA was efficient in evaluating frost damage in both young and adult plants, indicating its potential and application in different situations. The vegetation index MSR and MCARI2 indices were effective in assessing damage in one-year-old coffee plantations, whereas the SAVI, MCARI1, and MCARI2 indices were more suitable for visualizing frost damage in two-year-old coffee plantations.

Keywords: *Coffea arabica* L.; precision coffee; agrometeorology; remote sensing; index vegetation; frost damage

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1. Introduction

Brazil stands out as the largest coffee producer in the world [1]. Coffee ranks second in the country's agricultural exports and is one of the most important sources of revenue for the Brazilian economy [2]. The state of Minas Gerais is the main coffee-producing region in the country, contributing approximately 70% of its area to Arabica coffee [3]. However, weather-related problems in some producing areas, such as below-average rainfall and severe frosts in June/July 2021, affected the first flowering and fruiting of Arabica coffee, reducing the production potential for the next Arabica crop for 2022/23, which is expected to drop 19.3% compared to the 2020/21 crop [4].

Coffee production is subject to adverse weather conditions and extreme events, such as frosts, which have been affecting farmers' ability to plan for the coffee harvest [5]. In Brazil, frost is a concern for farmers in the south-central region of the country, where the vast majority of coffee producers are located [6]. In these regions, frost events are mainly associated with climatic factors such as latitude, altitude, distance of the sea and topography [7]. Most coffee-growing areas in the Minas Gerais region are located in a predominantly undulating relief class and at high altitudes between 900 and 1100 m [8,9], where frost is more likely to occur [10].

Frost in coffee-growing areas is a microclimatic phenomenon. In sloping terrain, when the temperature drops below the freezing point of water, the cold air that accumulates at the surface tends to flow downwards to the bottom of slopes and accumulate into depressions or valleys [10,11]. The exposure of plants to low temperatures can lead to water freezing in the cell tissues, rupturing the cell walls and causing damage, which gives a burnt appearance to the plant [5]. As a result, plant growth and flowering are affected, coffee beans turn black, and their quality deteriorates in direct proportion to the severity of frost damage [12]. Damage to the plant causes decreased photosynthesis, leaf death or stem damage [13], and a reduction in coffee yield.

After frost occurrence, coffee crops need to be assessed in terms of their conditions through monitoring and detection of damage. This is crucial to quantify the stress and damage caused by this event, providing essential information to support decision making, such as whether there is a need to prune damaged plants and apply fertilizer to preserve the leaves that were not affected [14]. Currently, coffee growers and researchers manually investigate damage in affected areas, making it a great challenge to obtain accurate crop damage data. However, recent implementations of systems based on thermal and spectral imaging offer a non-destructive method to detect frost damage in plants, and are increasingly functional and essential for early detection which allows frost risk management [12].

There are a few studies that have used spectral response data of coffee plants to assess frost damage. [14] studied the potential use of multispectral images obtained by remotely piloted aircraft (RPA) to analyze and identify the damage caused by frost in six-year-old coffee plants under different frost risk and demonstrated that the vegetation indices showed a strong relationship with frost damage in coffee plants. The use of RPA has shown a differentiated view of crop fields, facilitating the dissemination of this technology in the field [2].

The remotely piloted aircraft system represents a typical application of a suborbital platform equipped with onboard sensors, which enables the acquisition of products at various resolutions. This makes it possible to obtain information capable of anticipating and predicting trends in plant behavior in response to the influences of various agronomic and environmental factors [15]. Applying this knowledge in coffee farming may allow farmers to practice practical field management, such as assessing damage to coffee trees caused by frost and it will also provide timely agricultural information for farmers [14].

There is limited detailed information in the scientific literature regarding the impact of frost on coffee plants at different ages and the correlation between plant responses and topographical variations. These findings may facilitate the implementation of effective strategies that enhance decision-making processes and intervention practices among coffee producers. The presence of agricultural risk management tools is necessary to guarantee the farmer's income and being able to continue their activities when extreme weather events occur [5].

The hypothesis of this study is that the use of vegetation indices obtained through images captured by a multispectral camera onboard a remotely piloted aircraft is an effective and feasible approach to identify and monitor frost damage to coffee plantations, regardless of the age of the plant and the topographic characteristics of the terrain. In this context, the purpose of this study was to evaluate the impact of frost on coffee plants using vegetation indices for plantations with different ages and in different topographic conditions.

2. Materials and Methods

2.1. Description of the Area

This study was conducted at Fazenda Bom Jardim, located in Santo Antônio do Amparo, in the western region of Minas Gerais, Brazil, at the geographical coordinates 21°00′58.9″S and 44°55′24.9″W, altitude of 950 m (Figure 1).

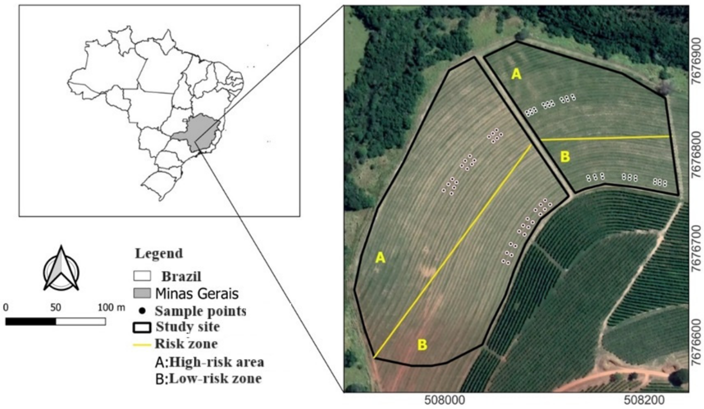


Figure 1. Geographical location of the study area. The sampling points are highlighted in black, and the climate suitability zones are separated by yellow lines as follows: A: high risk and B: low risk.

Santo Antônio do Amparo has the majority of its territory at altitudes between 900 and 1050 m, holding the largest coffee production area in the region, with 58% of the region consisting of undulating terrain creating a relief that rises and falls continuously, followed by gently undulating terrain with more gradual variations in height at 36.5%.This means that most coffee plantations are located in areas with less than a 20% slope [8]. Of the total area of the municipality with altitudes higher than 1050 m, approximately 46% of it is occupied by coffee farming. Coffee-growing areas predominantly occupy altitudes higher than 950 m [16]. The two areas evaluated have the following characteristics: The two-year-old crop area has an altitude of 937 m, a slope of 60°, and covers 19,959 m^2; the one-year-old crop area spans 24,475 m^2, with an altitude of 950 m and a slope of 62°. The region's climatic classification is Cwa, humid subtropical according to the Köppen-Geiser classification, with hot and humid summers and cold and dry winters, with average, minimum, and maximum temperatures of 20 °C, 14 °C, and 26 °C, respectively. The average total precipitation is 1400 mm.

2.2. Experimental Design

This study was conducted in two experimental areas, with different characteristics. Two planting areas, with two study factors, were used for evaluation: plant age and climate risk area associated with topography. Two plant ages were evaluated: coffee plants aged one year and two years; and two climate risk areas associated with topography were evaluated: low-risk area (coffee plants located on the slope of the terrain) and high-risk area (plants located in the valley area). To evaluate the damage levels in coffee plants, three blocks were delimited within each climatic risk area, and each block corresponded to ten plants.

For this study, two experimental coffee planting areas (*Coffea arabica* L.) were used. Two coffee cultivars were employed: the one-year area was cultivated with Catuaí Amarelo, and the two-year area was cultivated with Arara. Catuaí Amarelo is a hybrid developed in Brazil, specifically in Minas Gerais, resulting from the combination of the Caturra and Mundo Novo cultivar. Arara coffee is a cultivar originating from Brazil, arising from the natural crossbreeding between the Obatã and Catuaí Amarelo cultivar. In all planting areas, the spacing was 0.5 m between plants and 3.5 m between rows, totaling 5700 plants per hectare. The age of the plants was determined based on the time between the planting date and the frost occurrence, categorizing them as 1-year area and 2-year area.

The areas were divided based on the plant positions on the terrain according to the topography and climate risk, following the methodology proposed by [14], where the risk of plant damage is classified into low-risk (B) and high-risk (A) zones. The evaluated plants were georeferenced using GPS.

Before data analysis, the study area was classified with the objective of understanding the impacts of frost on coffee cultivation and recommending measures to minimize possible damage caused by this phenomenon. Following the methodology proposed by [14], the study area was subdivided into two distinct regions, each characterized by different levels of frost-related climate risk. These regions were classified as having "high" (A) and "low" (B) climate risk for the occurrence of frost, as illustrated in Figure 1.

This classification was established based on criteria that considered the variability of altitude and topography of the terrain, including variations in the slope of the terrain. Altitude variability refers to the difference in elevations found within a specific area. Terrain with different altitudes may have different microclimates and, consequently, be subject to different climatic risks, such as lower temperatures. In this context, the climate risk zones are described as follows: high risk: covers the lower third of the terrain, characterized by lower altitudes and a geographical configuration that makes the area more susceptible to adverse weather events, such as extremely low temperatures; low risk: comprises the upper third of the terrain, where altitudes are greater and the geographical configuration tends to reduce susceptibility to adverse weather events. Consequently, this area can be considered less vulnerable and therefore has a lower climate risk associated with frost.

2.3. Frost Damage Assessment and Plant Response

The frost occurred on 20 July 2021, with the minimum temperature recorded on a thermometer located in the study area being -1.7 °C. The assessment of frost damage in coffee trees was conducted following the methodology described by [14,17,18]. In this evaluation system, three independent expert researchers assess the three portions of each plant (upper, middle, and lower thirds), considering leaves and branches, assign scores from 0 to 10, and obtain an average score for each plant, which is then converted to a percentage. Parts of the plant exhibiting brown coloration and necrosis, physical characteristics caused by cell death due to freezing, were considered as damage.

The average values obtained by each researcher are grouped into damage classes; the scores from one to ten correspond to percentages of damage from 0 to 100%, as described in [14].

The coffee plants were evaluated by measuring: number of nodes per branch and number of damaged leaves. A measuring tape and a clipboard were used for the evaluations. Two branches (upper and lower) of the middle third of the plant were used for each evaluated plant to measure the variables.

2.4. Aerial Imaging and Image Processing

The first step was to generate the database containing images in digital format. The images were obtained using a remotely piloted aircraft (RPA) with a multispectral camera attached. The RPA used was the 3DR Solo commercial drone [19], equipped with four motors (quadcopter).

The images were captured by a Parrot Sequoia multispectral camera, which features an RGB sensor with a resolution of 16 megapixels (4608 × 3456) and four additional sensors with a resolution of 1.5 megapixels (1280 × 960) in the spectral bands of green at 550 nm and a Band Pass (BP) of 40, red (660 nm BP 40), red edge (735 nm BP 10), and near-infrared (790 nm BP 40). To eliminate atmospheric interference effects, radiometric correction plates were used during the flights.

The images were processed using Pix4Dmapper software version 4.5.6, student version [20], with parameter settings at the highest level, where the images were merged to generate orthomosaics for calculating vegetation indices. Pix4D software version 4.5.6 automatically calculates the positions and orientations of the original images through Bundle Block Adjustment (BBA). The images were georeferenced using control points previously collected in the field area near each evaluated plant by a differential GNSS (Trimble Navigation Limited, Sunnyvale, CA, USA) to improve orthomosaic precision. Based on the 3D point cloud obtained during BBA, a Digital Surface Model (DSM) is generated by interpolates to create gridded data. The orthomosaic corrects photography for tip and tilt and projects pixels to a map projection using elevation model [20]. The "Ag Multispectral" default model was used to generate the orthomosaic from individual spectral bands (green, red, red edge, and near-infrared). The calibrated reflectance panel corrected the image reflectance. The vegetation indices were calculated in QGIS. Image overlap was set at 80%, with a flight 90 m Above Ground Level and speed of 5 m/s, featured a pixel size of 3.75 µm, and a focal length of 3.98 mm. Image overlap is the link between the various sequential photos taken by the camera when producing the map.

2.5. Vegetation Indices

The vegetation indices were chosen based on the research of [14]. The vegetation indices of the images were computed using the Raster Calculator tool available in the Raster menu of QGIS 3.4.14-Madeira software [21]. After generating the vegetation indices, buffers were created around the georeferenced sample points from the field-collected data. The mean pixel values corresponding to each individual plant were extracted using the Zonal Statistics tool, with the mean value extracted from pixels within a 0.20 m radius from the center of each sampled plant to mathematically compare image values with field-collected damage data. Pixel values were exported in XLSX format, and the performance of vegetation indices in estimating frost damage in coffee plants was analyzed.

Each vegetation index is derived from different combinations of spectral bands, resulting in distinct values for each index. Therefore, to characterize leaf damage due to frost in coffee plants, several general approaches were adopted. These include identifying areas with significantly lower values in post-frost vegetation indices, comparing these values with established normal patterns for coffee crops, and validating through field inspections to confirm the extent of damage.

The vegetation indices were presented in Table 1. After processing the orthomosaics, the images were cropped only in the area of interest for the application of vegetation indices.

Table 1. Index vegetation calculated from the reflectance of multispectral bands of images.

Index Vegetation	Formulas	References
NDVI (normalized difference vegetation index)	(Nir − Red)/(Nir + Red)	[22]
NDRE (normalized difference red edge)	(Nir − RedEdge)/(Nir + RedEdge)	[23]
MTCI (meris terrestrial chlorophyll index)	(Nir − RedEdge)/(RedEdge − Red)	[24]
MSR (modified simple ratio)	((Nir/Red) − 1)/($\sqrt{}$((Nir/Red)) + 1)	[25]
GNDVI (green normalized difference vegetation index)	(Nir − Green)/(NIR + Green)	[26]
GCI (green coverage index)	(Nir/Green) − 1	[27]
NDWI (normalized difference water index)	(Green − Nir)/(Green + Nir)	[28]
MCARI1 (first modified chlorophyll absorption ratio index)	1.2 (2.5 (Nir − Red) − 1.3 (Nir − Green))	[29]
MCARI2 (modified chlorophyll absorption in reflectance index 2)	1.5 (2.5 (Nir − Red) − 1.3 (Nir − Green)) (Nir/Red)/$\sqrt{}$ (2Nir + 1) 2 − (6Nir − 5$\sqrt{}$Red) − 0.5	[29]
SAVI (soil adjusted difference vegetation index)	(1 + 0.5) ∗ ((Nir − Red)/(Nir + Red + 0.5))	[30]
OSAVI (optmized SAVI)	(Nir − Red)/(Nir + Red + 0.16)	[31]
CIrededge (Chlorophyll IndexRedEdge)	(Nir/RedEdge) − 1	[32]

Reflectance in the bands: (Nir) near infrared; (RedEd) between red and infrared (borderline red); (Red) red; (Green) green. Source: From the Author (2023).

2.6. Statistical Analyses

Data on frost damage, vegetative response, and the vegetation indices under study were compiled and exported to a Microsoft Excel spreadsheet. To analyze the relationship between damage and vegetation indices, the data were subjected to Pearson's correlation analysis (r) with a significance level of $p < 0.05$. The interpretation of Pearson's correlation values is categorized as follows: zero correlation for values equal to 0; weak correlation from 0 to 0.3; moderate correlation from 0.3 to 0.6; strong correlation from 0.6 to 0.9; and a very strong correlation of 0.9 to 1.0 [33]. The average values of the vegetation indices were calculated based on the average of the pixels located within a 0.20 m radius from the center of each plant.

Predictive linear regression models were used to evaluate the performance of vegetation indices in estimating frost damage to coffee plants in different climate risk zones. In these models, the vegetation indices were considered as independent variables, while the values representative of the damage in the different areas of climatic risk were dependent variables. The formula of simple linear regression is:

$$\mathrm{Y} = \beta_0 + \beta_1 \mathrm{X} * x \quad (1)$$

where

Y = dependent variable;
X = independent variable;
β_0 = intercept;
β_1 = angular coefficient;

Simple linear regressions were fit considering each vegetation index as the independent variable. However, using the 5% significance parameter, it was found this the adjustments did not satisfactorily estimate the damage, and in many cases, non-significant parameters were obtained for these models. Thus, it was necessary to apply multiple linear regression, which generalizes the simple linear regression model, allowing many terms in the model instead of just one intercept and one slope [34].

For the analysis of the data via the multiple linear regression model, all the vegetation indices presented in this study were included (NDVI, NDRE, MTCI, MSR, GNDVI, GCI, NDWI, MCARI1, MCARI2, SAVI, OSAVI, CIRededge). The multiple regression model was adjusted to explain the damage, verifying which variables were significant at the 5% significance level and estimating the values for the parameters. The formula of multiple linear regression is:

$$\mathrm{Y} = \beta_0 + \beta_1 * x + \beta_2 * x^2 \quad (2)$$

where

Y = dependent variable;
X = independent variables;
β_0 = intercept;
β_1, β_2 = coefficients of each independent variable;

The stepwise computational method was used for the selection of variables, which is a procedure for selecting or excluding variables based on an algorithm that checks the importance of the variables, including or excluding them from the model based on a decision rule. The model was also tested for multicollinearity between the variables, i.e., if two or more variables provide the same information, using the variance inflation factor (VIF). Residual analysis was performed to verify if any assumption of the model was violated. It was found that since the VIF is less than 10 for all explanatory variables in both models, the multicollinearity problem was not observed.

Residual analysis was performed to evaluate the suitability of the model and the homoscedasticity of the model, ensuring that the variance was constant. The symmetry of the data distribution was assessed. Finally, an analysis of the normality of the residual distribution was performed. These analyses provide valuable insights into the quality of the model and the reliability of the inferences derived from it. In addition to the graphical analysis, normality was confirmed by the Shapiro-Wilk test at the 5% significance level. The entire computational work was performed using the open-access software R, version 4.4.1 [35].

It was found that the assumption of random errors follows a normal distribution. This hypothesis was confirmed by the Shapiro-Wilk normality test, indicating that the errors indeed follow a normal distribution. Additionally, it was observed that the studied residuals have constant variances $Var(r_i) = 1$. Through these analyses, it was confirmed that the residuals exhibit a normal distribution and do not violate any assumptions of the model.

3. Results

3.1. Frost Damage in Climate Risk Zones

The results from the analysis of variance and mean test for the number of damaged leaves and nodes per branch of coffee plants are shown in Tables 2 and 3. Comparing different planting ages, the coffee plants exhibited higher damaged leaves values in high-risk zones (Tables 2 and 3). Regarding the number of nodes per branch, no significant differences were observed, regardless of the climate risk zone and the age of the plant.

Table 2. Number of damaged leaves (DL) and number of nodes per branch (NN) in one-year-old coffee plants in different climatic risk areas.

Climatic Risk Zones	Age of Plantation	
	DL	**NN**
	One year	
High risk	9 a	6 a
Low risk	4 b	6 a
Value (F)	0.05	0.66 ^{NS}
DMS	0.99	0.64
CV%	21.68	15.87

NS: not significant. Different letters in the same column indicate significant differences ($p < 0.05$) according to Tukey's test between climate suitability zones for each coffee plantation area. CV: coefficient of variation; LSD: least significant difference.

Table 3. Number of damaged leaves (DL) and number of nodes per branch (NN) in two-year-old coffee plants in different climatic risk areas.

Climatic Risk Zones	Age of Plantation	
	DL	**NN**
	Two year	
High risk	11 a	11 a
Low risk	5 b	12 a
Value (F)	3.88	0.45 ^{NS}
DMS	1.27	1.05
CV%	22.91	13.61

NS: not significant. Different letters in the same column indicate significant differences ($p < 0.05$) according to Tukey's test between climate suitability zones for each coffee plantation area. CV: coefficient of variation; LSD: least significant difference.

Specifically, for one-year-old coffee plants (Table 2), the average damaged leaves in high-risk zones was 9, compared to 4 in low-risk zones. For two-year-old plants (Table 3), those in high-risk zones showed an average of 11 damaged leaves, while those in low-risk zones maintained an average of 4 damaged leaves.

The results of the analysis of variance conducted on frost damage data across two climatic risk areas and different planting times were shown in Table 4. Coffee plants showed significantly higher frost damage in high-risk areas compared to low-risk areas. In the two-year-old coffee plants, high-risk and low-risk zones showed 50% and 12% frost damage, respectively. For the one-year-old coffee plants, high and low climate risk zones showed 88% and 6% damage, respectively. The high-risk area showed over

80% damage in one-year-old crops. When examining data dispersion using standard deviation, values remained below 10%.

Table 4. Frost damage (FD) and standard deviation (SD) of one-year-old and two-year-old coffee plants in different climatic risk areas.

Age of Planting	Climatic Risk Zones			
	Low Risk		High Risk	
	FD (%)	SD	FD (%)	SD
One year	6 Bb	2.3	88 Aa	7.7
Two years	12 Ab	4.85	50 Ba	8.66

Means followed by the same capital letter in the column and the same lowercase letter in the row did not significantly differ from each other according to Tukey's test ($p < 0.05$).

3.2. Maps of Vegetation Indices as a Function of Frost Occurrence

Maps of vegetation indices were generated to visualize the damage caused by frost in the study areas (Figures 2 and 3). The locations where the vegetation indices have the lowest values are represented by red and orange shades. This value characterizes the regions with the lowest vegetative vigor and, consequently, greater frost-damage thereby resulting in a reduction in the leaf area and productive capacity of the plant.

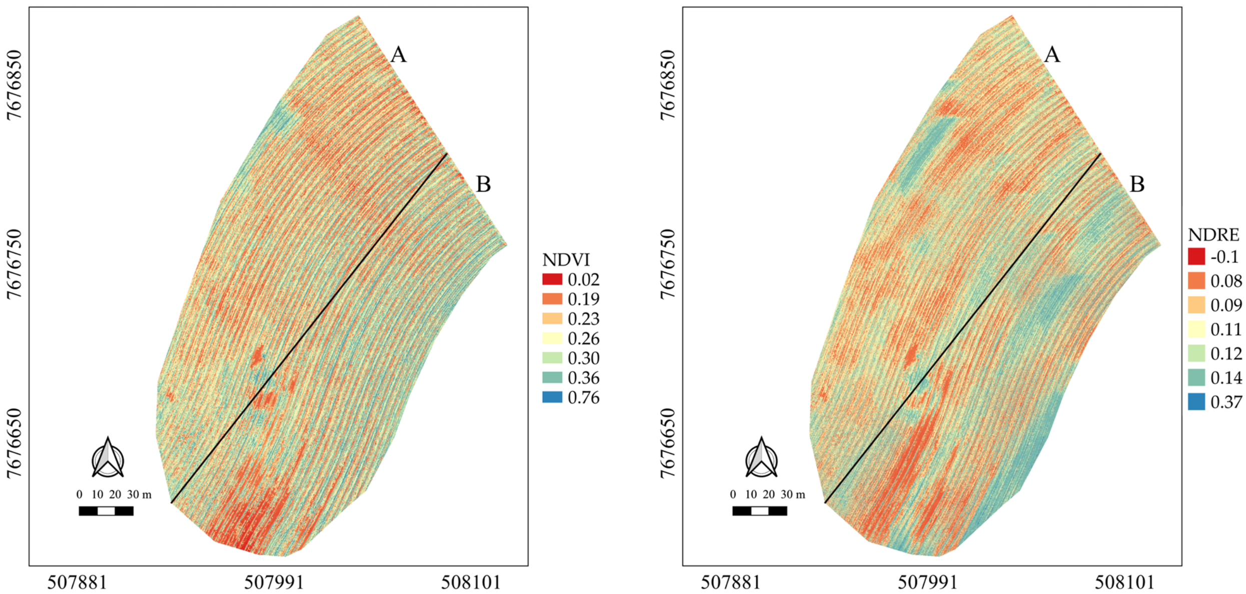
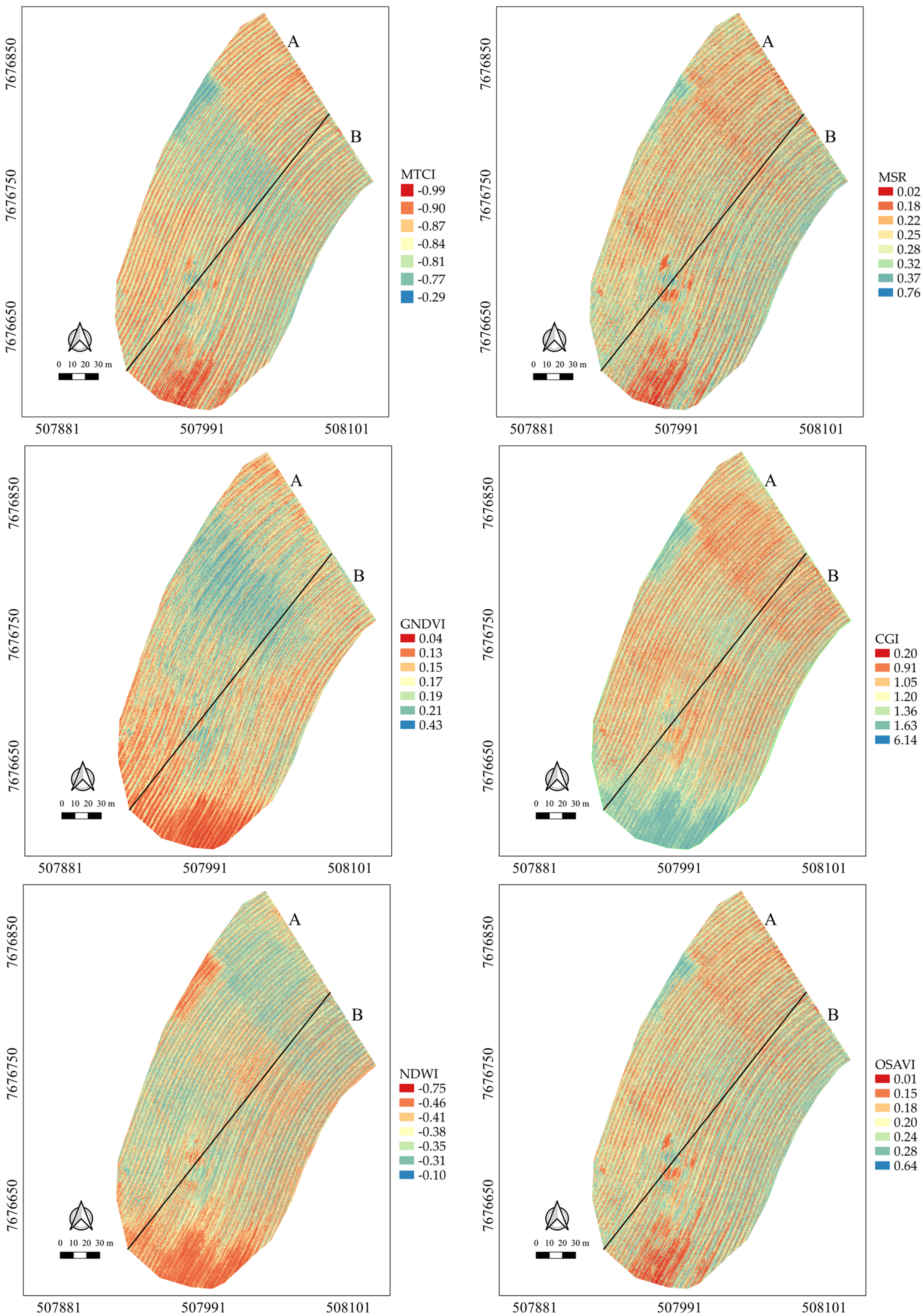


Figure 2. *Cont.*



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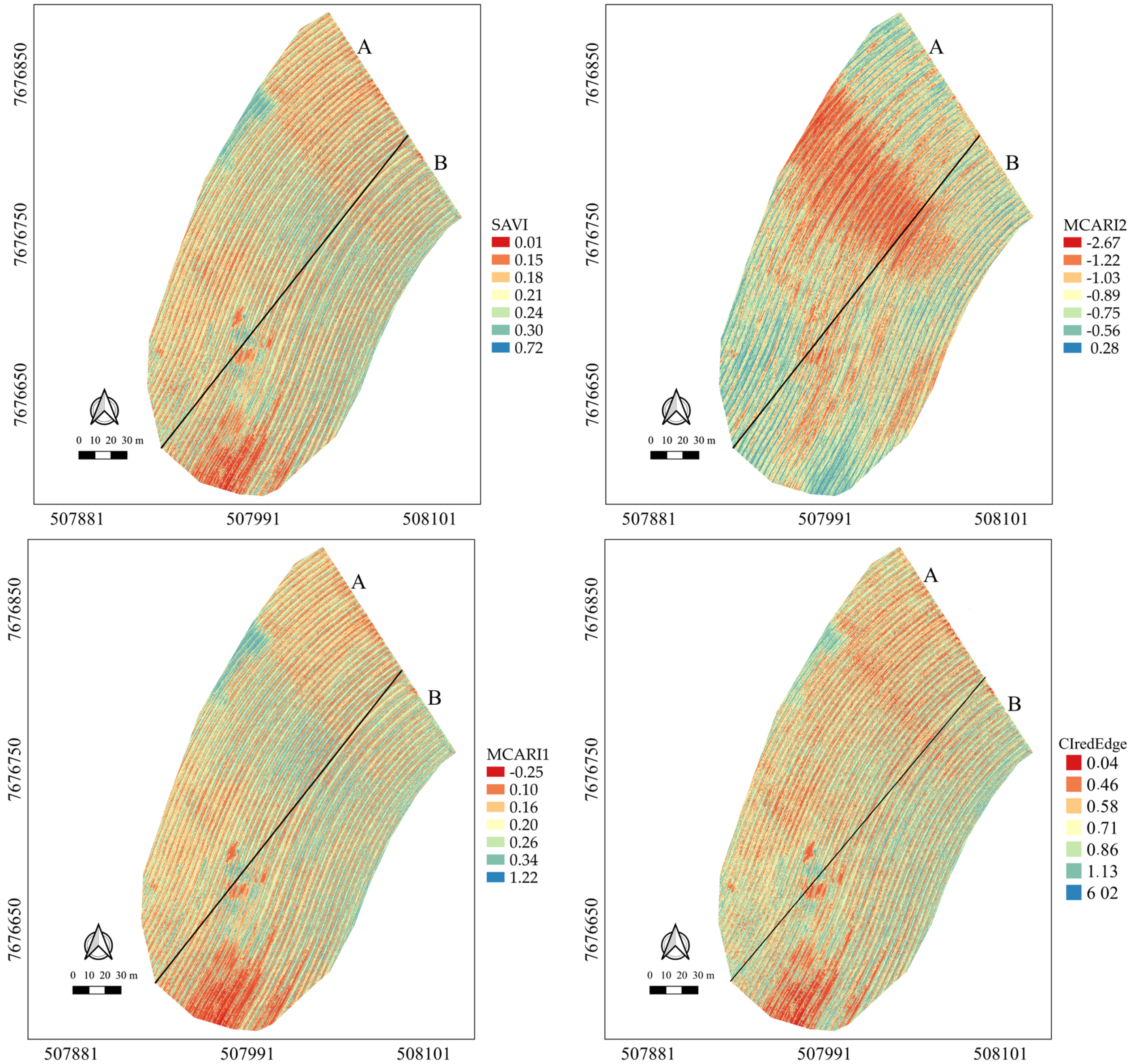

Figure 2. Maps of vegetative indexes in an area with one-year-old coffee plantations after the occurrence of frost. A: high-risk zone, B: Low-risk zone.

In the one-year-old coffee plants, the vegetation indices that most accurately reflect frost damage effects were NDVI, MSR, OSAVI, SAVI, MCARI1, and MCARI2 (Figure 2). These indices exhibited higher values in the low-risk zone compared to the high-risk zone. However, the NDRE, MTCI, GNDVI, CGI, and NDWI index maps did not clearly delineate the climate risk zones.

The maps of the spatial distribution of vegetation indices at two-years-old coffee plants can be seen in Figure 3. Vegetative indices NDVI, MSR, SAVI, OSAVI, and MCARI2 showed considerable spatial variations in values between the high-risk and low-risk zones.

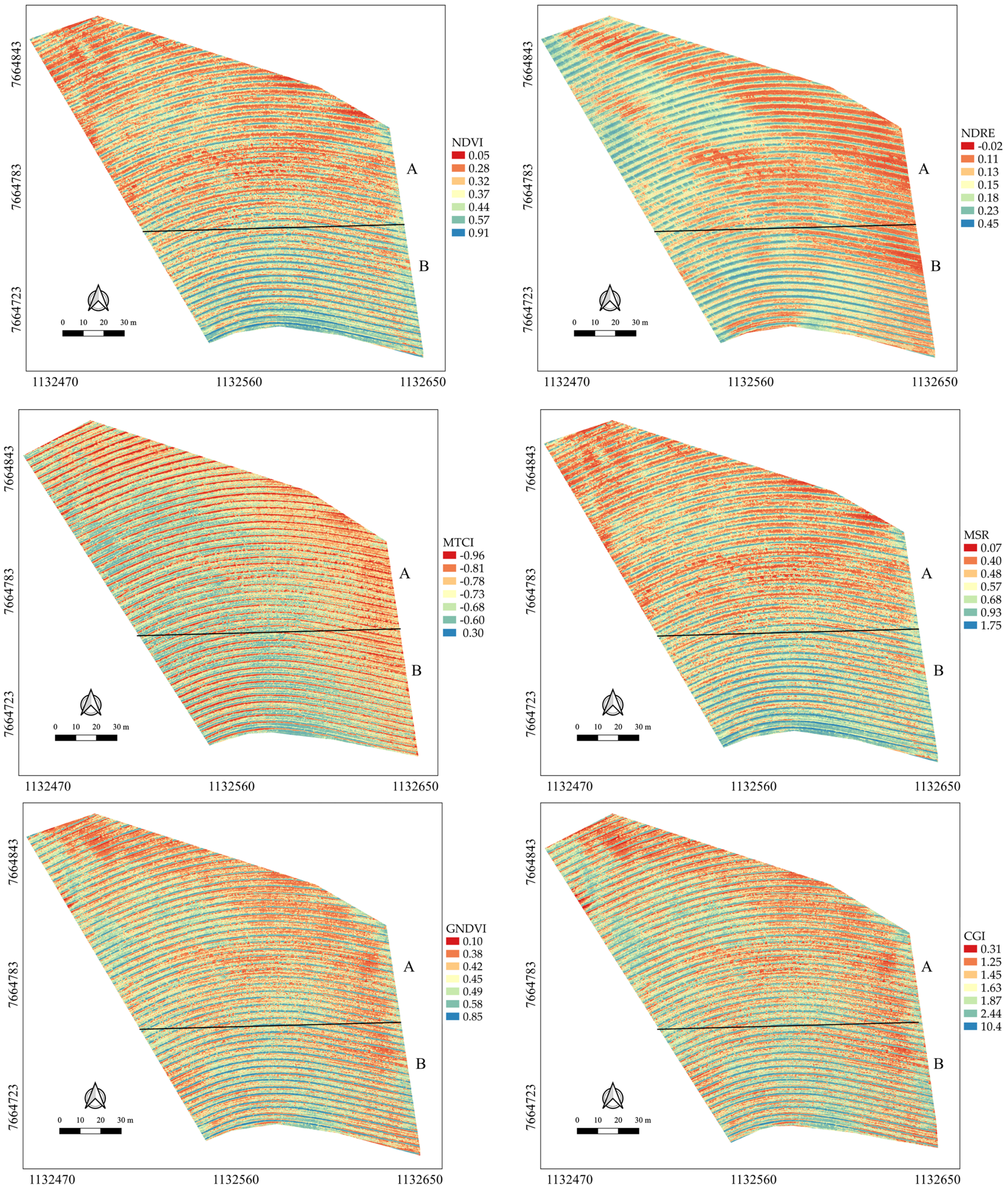

Figure 3. *Cont.*

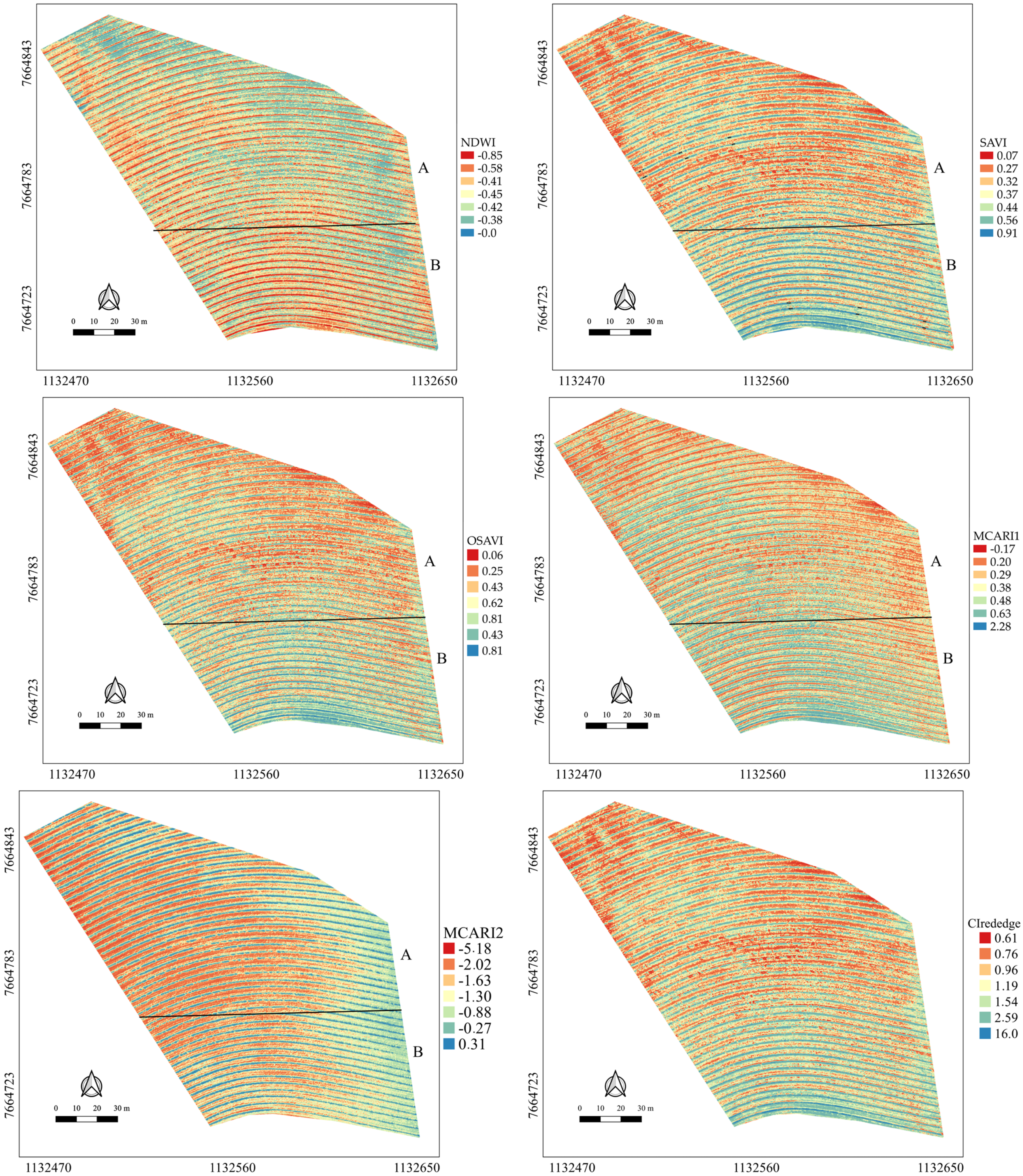

Figure 3. Vegetative index maps in an area with two-year-old coffee plantations after frost. A: high-risk zone, B: Low-risk zone.

3.3. Modelling of Frost Damage Generated by Vegetation Indices

3.3.1. Simple Linear Regression and Pearson's Analysis

Table 5 shows the estimates of the parameters for each vegetation index in one-year-old coffee plants, considering simple linear regression to describe frost damage and Pearson's correlation coefficient for each of them in different climate risk zones. The vegetation indices were related to the damage caused by frost; in some cases, this relationship was strong, while in others, the relationship was weak. The correlation analysis (r) showed that only the vegetation indices MCARI1, CIrededge, SAVI and OSAVI have a strong positive correlation (r > 0.60) with frost damage in the low-risk zone. The NDVI vegetation index has a moderate positive correlation (r > 0.50) with frost damage in the low-risk zone. In the high-risk zone, the NDRE and MTCI obtained a moderate negative correlation (r = −0.56).

Table 5. Estimates of the parameters of the simple linear regression model for the description of frost damage (FD) considering vegetation indices (VIs) in one-year-old coffee plants in different climatic risk zones and their respective correlation coefficients.

IsV	Risk	β_0	β_1	r	R^2
NDVI	Low	−5.38	23.20 *	0.53	0.28
	High	76.56 *	34.79	0.26	0.07
NDRE	Low	2.67	21.99	0.24	0.06
	High	120.01 *	−253.72 *	−0.57	0.33
MTCI	Low	6.78 *	−1.25	−0.04	0
	High	111.96 *	−142.39 *	−0.56	0.32
MSR	Low	−5.75	23.03	0.38	0.14
	High	104.18 *	−59.25	−0.38	0.14
GNDVI	Low	10.84 *	−46.49	−0.31	0.09
	High	75.60 *	88.02	0.25	0.06
CGI	Low	−1.19	2.818	0.37	0.14
	High	90.53 *	−1.94	−0.06	0
NDWI	Low	−7.66	−20.26	−0.31	0.09
	High	95.31 *	19.06	0.09	0.01
CIrededge	Low	−2.46	3.38 *	0.64	0.41
	High	83.71 *	5.15	0.14	0.02
SAVI	Low	−9.57	38.57 *	0.61	0.37
	High	86.49 *	6.48	0.03	0
OSAVI	Low	−11.21 *	42.08 *	0.64	0.41
	High	89.18 *	−2.44	−0.01	0
MACARI1	Low	−6.51 *	26.07 *	0.77	0.60
	High	86.51 *	6.04	0.04	0
MACARI2	Low	6.32 *	−4.08	−0.17	0.03
	High	94.59 *	21.87	0.41	0.16

* significant up to 5%.

Furthermore, the metric R^2 (coefficient of determination) was used to facilitate the interpretation of the model results. The closer the R^2 values are to 1, the greater the confidence in the interpretation of the relationship between the vegetation indices and frost damage. Among all the vegetation indices listed in Table 5, only MCARI1 showed a strong correlation (r = 0.77) and a coefficient of determination closer to 1 (R^2 = 0.60) in the low-risk zone.

Regarding data of the parameters for each vegetation index in two-year-old coffee plants, can be seen in Tables 6 and 7. Furthermore, it was observed that in the models (Tables 5 and 6) with the parameter β_1 set to the 5% significance level, performance was best when the correlation between the vegetation index and the damage was strongest.

Table 6. Estimates of the parameters of the simple linear regression model for the description of frost damage (FD) considering vegetation indices (VIs) in two-year-old coffee plants in different climatic risk zones and their respective correlation coefficients.

IsV	Risk	β_0	β_1	r	R^2
NDVI	Low	2.72	11.32	0.08	0.01
	High	99.39 *	−70.43	−0.34	0.11
NDRE	Low	29.97	−51.2	−0.14	0.02
	High	26.6	76.48	0.17	0.02
MTCI	Low	6.7	7.16	0.08	0.01
	High	47.14	4.01	0.03	0

Table 6. *Cont.*

IsV	Risk	β_0	β_1	r	R^2
MSR	Low	−9.41	15.13	0.27	0.07
	High	66.66 *	−14.37	−0.20	0.04
GNDVI	Low	4.64	10.08	0.08	0.01
	High	60.93	−16.78	−0.07	0.01
CGI	Low	12.78	−0.19	−0.04	0
	High	37.20	2.47	0.14	0.02
NDWI	Low	17.60	8.07	0.07	0.01
	High	19.03	−42.91	−0.09	0.01
CIrededge	Low	11.40	0,03	0.01	0
	High	89.57 *	−7.78	−0.33	0.11
SAVI	Low	−12.83	30.99	0.21	0.05
	High	197.07	−205.66	−0.36	0.13
OSAVI	Low	16.56	−8.05	−0.09	0.01
	High	4.503	78.87	0.26	0.07
MACARI1	Low	13.70 *	−2.57	−0.09	0.01
	High	34.28 *	18.27	0.39	0.15
MACARI2	Low	15.71 *	6.25	0.30	0.09
	High	38.36 *	−21.22	−0.40	0.16

* significant up to 5%.

Table 7. Pearson's correlation coefficient (r) for the frost damage (FD) and each vegetation index, for 1-year and 2-year plants.

Isv	1-Year-Old Plants	2-Year-Old Plants
NDVI	−0.83	−0.75
NDRE	−0.74	0.13 NS
MTCI	−0.83	−0.39
MSR	−0.95	−0.70
GNDVI	0.79	−0.43
CGI	−0.93	−0.37
NDWI	0.93	0.42
CIrededge	−0.92	−0.74
SAVI	−0.91	−0.79
OSAVI	−0.93	−0.33
MCARI1	−0.87	0.21 NS
MCARI2	−0.73	0.23 NS

NS: not significant.

3.3.2. Multiple Regression Analysis

The MSR, CGI, NDWI, CIrededge, SAVI and OSAVI indices showed a strong negative correlation ($0.9 < r < 1.0$) with frost damage in the one-year-old coffee plants (Table 7). In the two-year-old coffee plants, there was a strong negative correlation ($0.6 < r < 0.9$) for the NDVI, MSR, CIrededge and SAVI indices (Table 7).

To obtain estimates of frost damage considering the vegetation indices as explanatory (independent) variables, a multiple linear regression model was fitted considering all the indices. Then, the stepwise computational method was used, and the selected models were as follows:

For 1-year-old coffee plants:

$$\text{Frost damage} = 138.835 - 248.459 * \text{MSR} - 48.580 * \text{MCARI2} \tag{3}$$

$$R^2 = 92.89\%$$

For 2-year-old coffee plants:

$$\text{Frost damage} = 265.29 - 341.29 * \text{SAVI} + 50.79 * \text{MCARI1} + 32.11 * \text{MCARI2} \tag{4}$$

$$R^2 = 76.44\%$$

In the fitted model (1) for 1-year-old plants, the MSR and MCARI2 were found to be the most adequate vegetation indices to describe frost damage, with a coefficient of determination of 92.89%. For the adjusted model (2) that was developed for 2-year-old plants, the most appropriate vegetation indices to describe frost damage were SAVI, MCARI1 and MCARI2, with a coefficient of determination that explains 76.44% of variability in the data.

4. Discussion

4.1. Frost Damage and Relationship between Plant Age and Topography

The results obtained in this study showed that there was variation in the effect of frost on the plant's response depending on age and topography. Among the differences observed, the most impactful is related to the climate risk zone, indicating the importance of topography on coffee crops. This is justified by the impact observed in two-year-old plants in high-risk zones that had a 175% higher average of damaged leaves than those in low-risk zones. Similarly, one-year-old plants in high-risk zones had 125% higher values compared to those in low-risk zones.

The findings highlight the critical influence of topographical features in delineating areas susceptible to frost damage. This susceptibility is intricately linked to site-specific variables such as minimum temperature thresholds, plant phenology, and elevation [36]. This insight is vital for coffee producers, providing essential guidance for decision making and agricultural planning [14]. This study emphasizes the importance of avoiding lowland areas or regions with high frost risk for cultivation, as frost events can induce leaf necrosis and senescence, resulting in a diminished leaf area and reduced capacity for light interception. Consequently, this decline in photosynthetic efficiency leads to decreased productivity, culminating in lower yields during the coffee harvest season [37].

Significant differences in frost damage were observed between high and low climate risk zones, as well as across different planting times. In a related study, [14] reported increased frost damage in six-year-old coffee plants located in high climatic risk zones, with 45% of the leaf area being affected. These findings suggest that high-risk climate zones, determined by the topography, cause more substantial damage to coffee plantations, irrespective of planting time. The curvature of the land surface (convexity and concavity) is a critical factor in the formation of frost-prone areas [38]. On sloped terrains, dense cold air masses tend to flow and accumulate in the lowest areas [39]. Consequently, low temperatures and frost-prone zones often develop in valleys and low-lying regions [40,41]. Plants situated in these valley bottoms are exposed to prolonged periods of low temperatures, leading to more severe frost damage.

According to [38], the severity of frost damage is directly correlated with the extent of plant damage. Frost induces the formation of ice crystals within plant cells, leading to intracellular and extracellular freezing, the severity of which is influenced by the rate and extent of plant dehydration. Therefore, it is essential for producers to identify and classify areas based on topographical and climatic risks to implement appropriate management practices.

It is also important to consider obstacles such as trees, which can obstruct the flow of cold air, causing it to settle and further reduce temperatures, thus increasing the risk of frost [38]. In this study, due to the coffee plants' planting time, the plants were relatively short, allowing cold air to move easily toward the lower regions of the landscape, where temperature inversion is more pronounced, leaving a layer of cold air near the surface. As a result, shorter plants are more exposed to this cold air layer.

This information is crucial for crop management strategies, including pruning and fertilization, to preserve undamaged leaves [14]. Frost events have a direct impact on production costs, as higher mortality rates in coffee plantations necessitate increased replanting expenses. According to [42,43], decisions regarding replanting are based on the extent of tissue damage to the leaves and stem.

In such cases, the decision is not merely about pruning or fertilization but rather about plant survival and the potential need for replanting. If some plants perish, producers must decide whether to replant or retain surviving plants and wait for regrowth. The threshold for leaf damage that necessitates replanting after frost varies, influenced by factors such as the plant's recovery capacity, coffee variety, local conditions, and available resources. In some cases, if the majority of leaves are damaged but the roots and main stem remain healthy, the plants may recover over time. However, if the damage is extensive and plants show no signs of recovery after an adequate period, replanting may be necessary. This study identified the need to replant part of the one-year-old crop in high-climatic-risk areas.

The results emphasize that selecting planting sites that avoid low-lying areas prone to cold air accumulation has emerged as an effective strategy for mitigating risks. Additionally, implementing protective measures such as covering plants during frost periods can safeguard reproductive buds. This research provides a valuable foundation for informed decision making and the adoption of practices aimed at minimizing frost damage, thereby enhancing coffee production efficiency.

4.2. Maps of Vegetation in Relation to Frost Leaf Damage

The information generated through the maps allowed for the observation of spatial variability in frost damage. Additionally, the vegetation indices exhibited differential responses in plant monitoring. According to [14], the modified simple ratio (MSR) index effectively estimates frost damage in coffee plants, indicating that the visible spectral region is directly associated with frost damage, likely due to color changes in the leaves caused by freezing.

As noted by [28], the normalized difference vegetation index (NDVI) utilizes reflectance from the red and near-infrared (NIR) bands, with the red band located in the chlorophyll absorption region and the NIR band positioned in the high reflectance zone of the vegetation canopy. Consequently, NDVI tends to saturate when the leaf area index (LAI) is high. In this study, NDVI was effective in detecting frost damage in the two planting areas, likely due to the lower LAI of the young plantings. According to [44], evaluating the capacity of vegetation indices to spatially identify frost damage in cover crops, the authors achieved satisfactory results using indices based on the red, red-edge, and NIR regions of the reflectance spectrum; among these, NDVI proved successful. Similarly, [36] reported positive outcomes with NDVI in detecting canopy damage caused by frost in European beech (*Fagus sylvatica* L.) plantations. In the literature, NDVI is considered more sensitive to frost damage than other indices. For instance, [45] demonstrated that NDVI is capable of detecting frost damage in sugarcane. Despite these promising results, it is important to note that the developmental stage and type of crop in this study differ from those in the referenced studies.

The spectral variations depicted on the maps may aid in identifying areas with greater frost stress and guide planting management toward preventive and treatment practices in different climate risk zones. Studies utilizing suborbital remote sensing to monitor frost damage in coffee crops are limited. According to [46,47] detected frost damage in vegetation using satellite data; however, the use of satellite imagery is still constrained by spatial and temporal resolution as well as cloud interference. From a practical perspective, assessing frost damage in localized regions requires more precise indicators at finer temporal scales and refined data with higher spatial resolution [47]. The tool developed in this study is highly relevant and could significantly contribute to agricultural planning, particularly in rural financing and insurance applications.

Suborbital remote sensing has great potential as a tool to be incorporated into preventive and treatment management practices in coffee plantations located in frost-associated climate risk zones. The maps showed the variability of damage and highlighted the different climate risk zones. Therefore, the results of this study are encouraging in the detection of damage caused by frost. New evaluations should be performed combining vegetation indices involving additional analyses to improve the quality of regressions between the vegetation indices and the measured damage.

4.3. Modelling of Frost Damage Generated by Vegetation Indices

Before proceeding with the regression model, Pearson's correlation coefficient (r) between the frost damage variables and each vegetation index was calculated. For this adjustment, the indices were considered globally, disregarding the climate risk zones. This approach allows for a broad evaluation of the relationship between vegetation indices and frost damage, without the influence of segmentation by specific areas.

These results indicate a robust and inversely proportional association between these vegetation indices and the occurrence of frost damage, providing valuable information for understanding the response patterns of plantations to the frost phenomenon at different coffee plantation ages.

Analyzing the data as a whole, the vegetation indices performed better in the two-year-old planting in the high-risk zone, highlighting the sensitivity of the indices in identifying damage across different planting times and risk areas. Moreover, it was found that the simple regression model does not satisfactorily describe the damage. Therefore, multiple regression analysis was conducted to better estimate the damage using vegetation indices.

Based on the results, a very good estimate was observed using multiple regression, with an R^2 value of 92.89% for the model obtained for 1-year-old coffee plants. This highlights the importance of analyzing the data in an integrated manner and considering more than one vegetation index.

MCARI1 and MCARI2 are indices that capture variations in chlorophyll content in plants. The photosynthetically active green leaf area index is used to estimate biophysical traits [48]. In the case of MCARI2, a soil interference smoothing factor was inserted and developed to optimize the sensitivity of the index [29]. This explains why the MCARI2 index had better performance. In the one-year-old coffee, the plants are smaller and have smaller leaf area so the soil is more exposed.

The effectiveness of vegetation indices varied depending on their sensitivity in detecting damage across different planting ages. The data indicate that MSR and MCARI2 can support decision making in younger plantations, whereas SAVI, MCARI1, and MCARI2 indices are more suitable for older plantations.

5. Conclusions

The utilization of PRA proved to be an important tool for evaluating spatial variability and frost damage in coffee crops using vegetation indices. Furthermore, it is possible to highlight that the use of PRA was efficient in evaluating frost damage in both young and adult plants, indicating its potential and application in different situations. The MSR and MCARI2 indices were effective in assessing damage in one-year-old coffee plantations, whereas the SAVI, MCARI1, and MCARI2 indices were more suitable for visualizing frost damage in two-year-old coffee plantations. The vegetation index-based model allowed for the estimation of frost damage in high- and low-climate-risk areas.

Variations in frost damage were observed based on planting age and topography conditions. Coffee plantations with one-year and two-year-old exhibited the highest percentage of frost damage in high-risk climate zones. For one-year-old plants with damage exceeding 80%, replanting the area is recommended. In contrast, for the two-year-old area, pruning affected plants and fertilizing the area are recommended measures to enhance plant recovery. As a preventive measure, producers should avoid cultivating coffee in areas with high climate risk, particularly those at the bottom of slopes in depressions or valleys (lowland areas).

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